Future Position Prediction for Pressure Refuelling Port of Commercial Aircraft

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MSc
Academic Year: 2023–2024

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This thesis is submitted in partial fulfilment of the requirements for the degree of MSc.

Academic Integrity Declaration

I declare that:

- the thesis submitted has been written by me alone.
- the thesis submitted has not been previously submitted to this university or any other.
- that all content, including primary and/or secondary data, is true to the best of my knowledge.
- that all quotations and references have been duly acknowledged according to the requirements of academic research.

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Abstract

Replace with your abstract text of not more than 300 words.

Keywords:
Replace with at least 6, semicolon seperated keywords (not contained within the thesis title) – this makes the thesis searchable.

Acknowledgements

The author would like to thank …

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List of Abbreviations

ML	Machine Learning
DL	Deep Learning
AI	Artificial Intelligence
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
EKF	Extended Kalman Filter
AAGR	Autonomous Aircraft Ground Refueling
AGR	Aircraft Ground Refueling
UAV	Unmanned Aerial Vehicle
AAR	Autonomous Aerial Refueling
DGPS	Differential Global Positioning System
SVM	Support Vector Machine
HOG	Histogram of Oriented Gradients
SOTA	State-of-the-Art
AIS	Automatic Identification System
GPS	Global Positioning System

Chapter 1

Introduction

Ground pressure refuelling is a standard method used to refuel commercial aircraft safely and efficiently. This process involves using a hydrant system, which consists of underground fuel pipelines connected to a network of fuel hydrants located at aircraft parking positions [5]. The hydrant system is supplied with fuel from storage tanks, typically located near the airport [13].

When an aircraft is ready for refueling, a hydrant dispenser vehicle, also known as a hydrant truck or cart, is connected to the hydrant pit using a flexible hose [17]. The hydrant dispenser vehicle is equipped with a pressure control valve, a flow meter, and a filtration system to ensure that the fuel meets the required quality standards [3].

The refueling process begins by connecting the hydrant dispenser vehicle to the aircraft's fuel panel using another flexible hose [17]. The pressure control valve on the hydrant dispenser vehicle is then used to regulate the fuel pressure and flow rate, ensuring that the fuel is delivered to the aircraft at the appropriate pressure and volume [3].

One of the main advantages of pressure ground refueling is its efficiency. This method allows for high fuel flow rates, which can significantly reduce aircraft turnaround times [5]. Additionally, the use of underground pipelines eliminates the need for fuel trucks, reducing traffic congestion and the risk of accidents on the apron [13].

Safety is another critical aspect of pressure ground refueling. The hydrant system is designed with multiple safety features, such as emergency shutdown valves and leak detection systems, to minimise the risk of fuel spills and fires [3]. Moreover, the hydrant dispenser vehicles are equipped with safety devices, such as dead man switches and bonding cables, to prevent incidents during the refueling process [17].

Figure 1.1: Pressure Refuelling of a Commercial Aircraft. Source: Tom Boon/Simple Flying

The aviation industry is undergoing a significant transformation with the advent of intelligent airports based on highly automated systems. Among these, automated refuelling systems play a crucial role in ensuring efficient and accurate refuelling of aircraft. However, one of the main challenges of this automation process is the accurate detection of the aircraft's refuelling port, which is relatively small and can easily be obscured by other visual elements on or near an aircraft. Scanning the entire area of each video frame is both time-consuming and inaccurate. It is therefore essential to develop a more efficient and accurate method of locating the refuelling port.

This thesis aims to address this challenge by developing a new AI model that uses the temporal relationships between successive frames of a video to predict the location of the refuelling port in subsequent frames. By focusing the analysis on the most relevant areas of the video sequence, this approach has the potential to optimise both the speed and accuracy of the refuelling system.

Specific objectives of this thesis include conducting a comprehensive review of state-of-the-art object detection and tracking methods, designing and developing a real-time computer vision system capable of accurately detecting and tracking the pressurised refuelling port of a commercial aircraft, the implementation and evaluation of deep learning time series models for future position prediction, the integration of Extended Kalman Filtering (EKF) into deep learning models to improve the accuracy and robustness of future position predictions, and the development of a real-time framework for predicting the future position of the pressurised refuelling port.

By achieving these objectives, this thesis aims to make a significant contribution to the development of intelligent airport systems and to improve the efficiency and accuracy of automated refuelling systems at airports, while reducing computing power requirements. The proposed framework has the potential to be applied in various scenarios, such as different lighting conditions, angles and orientations of refuelling ports, making it a versatile and effective solution to the challenges of automated refuelling systems.

Chapter 2

Literature Review

2.1 Automated Refulling Systems in the Aviation Industry

2.1.1 Introduction to Automated Refuelling Systems

Automated refueling systems have gained substantial importance in the aviation industry due to their potential to enhance safety and efficiency. The concept of Autonomous Aircraft Ground Refueling (AAGR) emerged in the 1980s, with initial implementations featuring numbered markers near refueling ports to aid in image processing and robotic automation [18, 4, 14].

These systems streamline the refuelling process by using state-of-the-art mechanisms and technologies to ensure accuracy and speed. A key element is the pressurised fuel adaptor, which connects seamlessly to the aircraft [22]. Methods such as 'PosEst' have been proposed to capture and track objects in 3D, with the aim of increasing the safety and efficiency of refuelling tasks through autonomous systems [23].

In addition, autonomous in-flight refuelling technologies for Unmanned Aerial Vehicles (UAV-AARs) have also been developed to extend their range, endurance and payload capacity without significantly altering their original design. This technology overcomes limitations in fuel capacity and endurance, enabling UAVs to undertake longer missions [8].

2.1.2 Challenges in Automated Refuelling

The implementation of AAGR presents a number of challenges, including varying lighting conditions, different refuelling port designs and potential obstructions. Confidentiality issues associated with aircraft refuelling data, as well as the lack of standardised workflows, also complicate the deployment of advanced AAGR solutions, based on [14] data.

Accurately detecting and estimating the position of the fuelling adaptor is a major hurdle. Current methods that rely on artificial features often encounter occlusions and suffer from reduced reliability due to a low signal-to-noise ratio, particularly over long distances [23]. Variability in lighting, weather conditions and the physical state of the refuelling adapter further complicates detection and localisation [24]. Vision-based systems must operate in real time and with minimal computational load, adding a new layer of complexity.

The development of high-quality data sets for training and monitoring automated refuelling systems is another major challenge. Collecting and processing these datasets is often time-consuming and requires meticulous configuration [22].

2.1.3 Current Technologies and Methods

Visual measurement methods based on artificial features, such as spray marks or LEDs, are commonly used in today's automated refuelling systems. The VisNav system, developed by Valsek, uses light-emitting diodes emitting at different frequencies to locate the centre of a beacon, employing a Gaussian least squares differential correction algorithm to calculate the position of the [23] refuelling adaptor. Despite the advantages of these methods, they remain sensitive to occlusion and low signal-to-noise ratios at long distances.

Recent advances in Automatic Aircraft Ground Refuelling (AAGR) rely on computer vision, artificial intelligence and robotics to achieve high levels of automation. The integration of these technologies with Big Data has significantly improved the feasibility and accuracy of AAGR systems thanks to the creation of large datasets for training and validation. For example, an Aircraft Ground Refuelling (AGR) dataset comprising more than 3,000 images from 13 databases was expanded to more than 26,000 images after augmentation, enabling AGR scene recognition through image mining, augmentation and classification [14]. In addition, recent innovations have introduced hybrid datasets combining real and synthetic data for training and validating [24] systems. This approach offers a wide range of scenarios and conditions, improving the robustness and accuracy of automated refuelling systems.

Furthermore, in the field of autonomous aerial refuelling, current technologies rely mainly on vision-based systems and sophisticated control algorithms. These methods use a variety of sensors, including monocular and binocular cameras, to detect and track drugs and refuelling probes. Wang et al. [20] demonstrated the feasibility of real-time drug recognition and 3D localisation for autonomous aerial drone refuelling using monocular computer vision. In addition, Chen and Stettner [6] explored the application of 3D flash lidar for drug tracking [20]. The probe and drogue refuelling system involves the refuelling aircraft towing a refuelling hose with a drogue at the end, while the pilot of the receiving aircraft manoeuvres to insert the probe into the drogue. For unmanned aerial refuelling, this process is carried out autonomously. Although DGPS offers high location accuracy, it faces challenges such as lock-in problems and low bandwidth in air-to-air refuelling applications [26].

2.1.4 Future Directions and Innovations

Future progress in AAGR will depend on systematic research and improvements in training processes and classifier design. One promising approach is to use image style transformation technologies based on generative models to simulate changes in real-world visual conditions such as weather, lighting and camera angles [14]. However, these technologies need to be refined to become specific to aircraft ground refuelling scenarios.

Expanding the training datasets to encompass various aircraft models and exploring alternative filtering methods to reduce system delays are also key to future improvements. Ongoing technological developments are expected to minimise human intervention in refuelling tasks, paving the way for more efficient and accurate autonomous systems [23].

Validation of the results using other measurement methods, such as laser trackers, and testing of the systems developed on passenger aircraft under real conditions are essential steps. This research aims to ensure the reliability and applicability of automated refuelling systems in operational environments [24].

Advances in computer vision algorithms and hardware will be key to improving the accuracy and reliability of position measurements. Innovations in sensor fusion, combining data from various sources such as vision systems and Differential Global Positioning Systems (DGPS), could lead to more robust solutions. Improved real-time image processing capabilities and sophisticated filtering techniques, such as the Extended Kalman Filter (EKF), are likely to play a key role in the evolution of autonomous aerial refuelling technologies [26].

Further integration of advanced computer vision techniques and machine learning algorithms can significantly improve the accuracy and reliability of the refuelling process. The development of more sophisticated synthetic datasets that simulate a wider range of conditions and scenarios will improve the system's ability to handle real-world variations and anomalies [22].

By continually refining these systems, the aviation industry is one step closer to achieving fully autonomous and highly efficient refuelling operations, marking an important milestone in intelligent airport operations and advances in aviation safety.

2.2 Object Detection and Tracking in Computer Vision

2.2.1 Fundamentals of Object Detection

Object detection is an essential task in computer vision, involving the identification and location of instances of specific classes (e.g. humans, animals, vehicles) in digital images. The aim is to develop algorithms capable of accurately and efficiently determining the presence and location of these objects. Key performance metrics for object detection include classification accuracy, location accuracy and processing speed [27]. This fundamental technology underpins a range of applications such as autonomous vehicles, surveillance systems and robotics.

2.2.2 Techniques and Algorithms for Object Detection

The rapid development of deep learning has led to substantial advances in object detection, propelling it to the forefront of computer vision research. Object detection is an integral part of many other tasks such as instance segmentation, image captioning and object tracking [27].

Traditional object detection methods include techniques such as edge detection, shape matching, Haar cascades, histogram of oriented gradients (HOG) and support vector machines (SVM). Modern approaches are based on deep learning models such as convolutional neural networks (CNNs), region-based CNNs (R-CNNs) and the 'You Only Look Once' (YOLO) method. These advanced techniques have significantly improved detection accuracy and enabled real-time performance.

In specific applications such as autonomous aerial refuelling, new methods such as the one proposed in Zhong et al. [26] use monocular vision to estimate relative positions. This approach calculates coordinates by recognising beacons on the drogue, using image processing techniques and the Extended Kalman Filter (EKF) to improve robustness and increase detection frequency [26].

2.2.3 Challenges in Object Detection and Tracking

Despite significant progress, object detection still faces several major challenges:

- **Intra-class Variation:** Variations within the same object class due to factors like occlusion, lighting, pose, and viewpoint can significantly affect appearance, complicating accurate detection.

- **Efficiency:** Accurate detection models often require significant computational resources. As mobile and peripheral devices become more common, there is a pressing need for efficient object detectors [25].
- **Environmental Factors:** Varying lighting conditions, weather, and high-speed object movements further complicate detection and tracking. In applications like autonomous air refuelling, maintaining high precision during the docking phase is particularly critical [26].

2.2.4 Applications in the Aviation Industry

Object detection and tracking are essential in the aviation industry to improve the safety and efficiency of various operations.

For example, the paper of Zhong et al. [26] details its application to autonomous aerial refuelling (AAR) of unmanned aircraft. Using a monocular vision system supplemented by the EKF, the method ensures accurate measurements of the relative position between the receiver and the tanker aircraft during docking, enabling successful autonomous refuelling operations [26].

In addition, the paper of Wang et al. [20] presents a real-time method for drug detection in autonomous PD-UAV-AAR refuelling. Based on the Caffe deep learning framework with CNNs, this approach achieves high accuracy and robustness without depending on artificial features, making it suitable for complex aeronautical environments [20].

2.2.5 Recent Advances and Future Trends

The field of object detection has seen rapid advances, particularly with the proliferation of improved deep learning models. A comprehensive overview of these advances is provided in the review work presented in [25].

Recent innovations include the integration of deep learning techniques, which notably improve accuracy and robustness. The adoption of extended Kalman filters, as shown in the paper of Zhong et al. [26], improves the reliability of vision-based systems under dynamic conditions. Future trends may involve the development of more sophisticated algorithms and sensors to further refine detection and tracking performance.

In summary, continued advances in deep learning and related technologies promise to address existing challenges, improving the capabilities of object detection systems for a variety of critical applications, including those in the aerospace industry.

2.3 Deep Learning for Time-Series Prediction

2.3.1 Deep Learning Models for Time-Series Prediction

Time series prediction involves processing sequential data to predict future events or values. Various deep learning models have been applied to this task, requiring several preparatory steps such as collecting data, designating attribute types, dealing with inconsistencies and storing datasets. These datasets are usually classified into units of time such as seconds, minutes and hours, allowing the construction of metadata for machine learning [15].

The problem of locating future objects has been widely studied, particularly for static surveillance cameras, from a bird's-eye view. Early work used recurrent neural networks

(RNNs), including long-term memory networks (LSTMs) and managed recurrent units (GRUs), in an encoder-decoder format to encode past observations and decode future locations. Additional inputs, such as environmental information and semantic actions, were used to improve prediction accuracy. Alahi et al. [1] proposed a Social-LSTM to model pedestrian trajectories and interactions, further improving global context capture through a social pooling module [12]. Recent advances have taken advantage of generative models and attention mechanisms to handle complex scenes involving various interacting agents [12].

The article of Xu et al. [21] discusses various deep learning models used to predict time series. In particular, the work by Feng et al. [7] uses attentional recurrent networks to predict human mobility [21]. In addition, the paper highlights the use of BERT4Rec, which exploits bidirectional representations of transformer encoders for sequential recommendation tasks [21].

Several models for predicting ship trajectories have been proposed. Anderson considered ship trajectories as a one-dimensional Gaussian process and predicted smoothed trajectories by combining the dynamics with joint prior density and covariance matrices. Jiang et al. [10] used a polynomial Kalman filter for recursive trajectory prediction with minimal memory usage. kai Zhang et al. [11] adopted a spatial clustering method for prediction, using the DBSCAN model to cluster and denoise the original AIS trajectories. Rong introduced a probabilistic model describing the uncertainty of future ship positions through continuous probability distributions, which achieved high prediction accuracy [16].

2.3.2 Recurrent Neural Networks and Long Short-Term Memory Networks

Recurrent neural networks (RNNs), including long-term memory networks (LSTMs) and managed recurrent units (GRUs), have shown promise for predicting the future locations of traffic agents [12]. However, many RNN-based models suffer from performance degradation over time due to their reliance on recurrent prediction of future bounding boxes from previous outputs. The Fusion-GRU model addresses these challenges by exploiting multiple sources of information, such as location scale data, monocular depth information and optical flow data. This approach improves representation learning by capturing the complex interactions between the various information cues, thereby improving the future localisation of traffic agents in congested and risky driving scenes [12].

RNNs are powerful for processing sequence information and making time-based predictions. Hochreiter et al. improved the structure of the RNN unit, introducing the LSTM model to solve the problems of gradient fading, gradient explosion and insufficient information memory through a gating [16] mechanism. LSTMs make efficient use of long-range temporal information, which is useful in a variety of prediction tasks. However, BP neural networks and SVMs also exist for trajectory prediction, but have limitations such as weaker handling of non-linear problems and susceptibility to local extrema [16].

2.3.3 Transformer models for sequence prediction

Recent research has used transform-based methods for estimating the future location of traffic citeFusionGRU agents. Despite advances in deep learning for locating objects in typical driving scenarios, predicting locations in risky scenarios remains challenging due to abrupt changes in motion and interdependencies between successive images [12].

The Transformer model, introduced by Vaswani et al. [19], has revolutionised sequence modelling with its efficient and powerful network structure. For mobility prediction, Transformer models are increasingly recognised for addressing the challenges of predicting individual mobility patterns. The Hong et al. [9] study shows how Transformers are tackling:

- **Multiple Periodicities:** Individual location visitation patterns exhibit multiple periodicities (e.g., daily, weekly), which vary considerably across individuals. The multi-head self-attention mechanism in transformers allows the network to focus on multiple steps in the input sequence, effectively capturing these periodicities.

- **Long-term Dependencies:** Human mobility depends on behaviors conducted days or weeks before. The design of the transformer model enables efficient learning of these long-term dependencies.

This study proposes a Transformer-based model that uses historical travel behaviour to predict individuals' next locations. The model learns mobility transition patterns from historical sequences of location, temporality and mode of travel, enabling it to achieve peak performance in next location prediction tasks.

- **Joint Learning:** The model jointly learns the next location and the next travel mode, which improves the prediction performance for both tasks.

- **Empirical Validation:** Extensive experiments on two real-world GPS tracking datasets show that considering additional aspects of travel behavior significantly increases the performance of next location prediction.

In summary, the transformer model's ability to capture complex spatio-temporal dependencies and long-term patterns makes it a powerful tool for sequence prediction tasks, including those in the domain of human mobility.

2.3.4 Applications in the Aviation Industry

2.3.5 Challenges and Future Research Directions

Despite significant advances, several challenges persist in deep learning models for time series prediction. One of the main challenges is the performance degradation of RNN-based models over time, addressed by models such as Fusion-GRU, which exploit multiple data sources for better representation [12]. Accurate prediction in risky driving scenarios, involving sudden or abrupt changes in motion, is still unresolved. Future research could focus on improving model robustness in these scenarios and integrating additional data sources to improve prediction accuracy [12].

The article of Arora et al. [2] identifies several challenges in location prediction using machine learning, highlighting the need for trajectory data quality and extensive pre-processing. Future research could incorporate semantic information to improve prediction accuracy, taking advantage of ensemble techniques and overcoming data limitations. The ensemble architecture recommended in the paper shows a significant reduction in mean distance error compared to reference models [2].

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Appendix A

Ethical Approval Letter

Insert your Ethical Approval Letter as the first appendix.

Appendix B

Extra Data

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